CONTRAST ENHANCEMENT BY USING NONLINEAR DIFFUSION FILTERING AND LHM

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Abstract
To enhance the visual quality of an image that is degraded by uneven light, an effective method is to estimate the illumination component and compress it. Some previous methods either have defects of halo artifacts or contrast loss in the enhanced image due to incorrect estimation. In this paper, we discuss this problem and propose a novel method to estimate the illumination. The illumination is obtained by iteratively solving a nonlinear diffusion equation. During the diffusion process, surround suppression is embedded in the conductance function to specially enhance the diffusive strength in textural areas of the image. The proposed estimation method has the following two merits: First, the boundary areas are preserved in the illumination, and thus, halo artifacts are prevented; and second, textural details are preserved in the reflectance to not suffer from illumination compression, which contributes to the contrast enhancement in the result. Experimental results show that the proposed algorithm achieves excellent performance in artifact removal and local contrast enhancement.

Index Terms — contrast; image enhancement; illumination estimation; nonlinear diffusion; halo artifacts;

I. INTRODUCTION
The observed image is the multiplication of two components, namely, illumination and reflectance, which are described as intrinsic images in [1]. In a real scene, the illumination component is usually nonuniform and has a high dynamic range, whereas the reflectance reveals the details of the objects in the image. A digital acquisition device such as a consumer digital camera often suffers from varying light conditions because of its much narrower dynamic range than that of the illumination. The captured image could contain both underexposed and overexposed regions and has low local contrast in both areas. Therefore, an enhancement algorithm that focuses on addressing the illumination problem is required to enhance the image’s visual quality. There are several types of contrast enhancement algorithms that have been proposed, such as histogram equalization [2], [3] and perceptual enhancement [4], [5], among others. A large set of these algorithms are inspired by Retinex, which was originally a color constancy model that mimicked the color appearance of the human visual system [6]. Algorithms of this type typically decompose the image into a low frequency component denoted as illumination and a high frequency component denoted as reflectance. The local contrast is enhanced by compressing the illumination or simply extracting the reflectance as the final result.

Among the Retinex-inspired algorithms, a widely used version is the center/surround algorithm [7]-[13]. This type of algorithm estimates a smoothed version of the image and subtracts it from the original image to improve the contrast. The methods differ in the types of filters that are adopted to blur the image. The SSR (single-scale Retinex) [7] and MSR (multi-scale Retinex) [8] utilize a Gaussian filter to smooth the image. A modified method is the bilateral filter, whose weighting coefficients are a combination of spatial closeness and pixel value similarity [9], [10]. This method preserves the edges well in the illumination and avoids halo artifacts in the enhanced...
result. Recently, Wang designed a “bright-pass” filter to estimate the illumination, in which the weights were calculated by the frequency in the spatial domain of the relationship between the central pixel and its neighboring pixels [13].

In this paper, a novel contrast enhancement algorithm for images with uneven illumination is proposed. First, an illumination-reflectance decomposition is performed on the original image. The method used to estimate the illumination component is based on nonlinear diffusion filtering. To better match the illumination estimate to the assumption made in this paper, a texture suppression mechanism is introduced to improve the performance of the filtering. Then, a logarithmic compression is conducted on the estimated illumination, which is followed by the final recombination of the reflectance and the compressed illumination to obtain the final result. Experiments show that the effectiveness of the algorithm is threefold: local contrast enhancement, global brightness promotion, and avoidance of halo artifacts.

II. ILLUMINATION ESTIMATION BASED ON NONLINEAR DIFFUSION

The flexibility and effectiveness of nonlinear diffusion exist in that its smoothing performance can be tuned by changing the equation formation and determining a different set of parameters. For example, it can smooth undesired information while respecting region boundaries and other structures in the image, as long as some crucial parameters are set appropriately. On the other hand, it tends to yield piecewise-constant-like images before it finally arrives at the globally constant solution. The above features are potential merits for estimating the expected illumination in this paper. In this section, the nonlinear diffusion is first introduced. Then, the texture suppression used to improve the smoothing properties for better handling of the expected illumination is described. Finally, the entire nonlinear diffusion method for illumination estimation as well as the acceleration strategy is presented in detail.

\[
\frac{\partial I(x,y)}{\partial t} = \text{div}\{g(\|\nabla I(x,y)\|) \cdot \nabla I(x,y)\}
\]

with a Neumann boundary condition of

\[
\partial_n I(x,y) = 0 \quad \text{on} \quad \partial \Omega
\]

Formula (1) denotes the evolution of image \(I(x,y)\) per unit time. Here, \(g(.)\) is the conductance function that controls the diffusivity; it is set to be a monotonically decreasing function of an image gradient module \(\|\nabla I(x,y)\|\) so that the diffusivities are strong in areas that have small gradients and weak in areas that have large gradients. As the evolution proceeds, the areas that have large discontinuities are preserved, whereas those that have small discontinuities such as plain areas or noise are smoothed out. Formula (2) indicates that there is no orthogonal diffusion to the image borders \(\partial \Omega\). In theory, a globally constant image is the solution of the equation.

Fig. 1. Surround suppression. (a) Model of surround suppression. (b) Suppression effects in different areas.
Fig. 2. Effects of texture suppression. (a) Original image. (b) Gradient module of (a). (c) Boundary template.

Although the original model of nonlinear diffusion yields an impressive result for selective smoothing, it is theoretically ill-posed. This problem occurs mainly because, in most cases, the variational function that is correlated with (1) is not convex. Forward and backward diffusions simultaneously exist, which indicates that there are potentially multiple solutions to the equation. Fortunately, various regularization strategies in the research are sufficiently good to turn it well-posed for practical use.

With regard to the task of illumination estimation, directly applying equation (1) cannot effectively obtain the expected illumination. The reason is that its criterion for selective smoothing depends on the gradient module, $|\nabla I(x,y)|$ which is unable to fully demarcate between texture edges and boundary edges. Some of the textures could have higher gradients than some boundaries and, hence, weaker diffusivities.

b). Texture Suppression

Studies of neurophysiology have found that the human visual system has a mechanism to make prominent the contours of observed objects. The main reason is that when recognizing objects by judging their contours, the human visual system has a surround suppression mechanism to suppress the disturbing texture information. This mechanism and its effects are shown in Fig. 1. It is basically divided into two areas: an annular inhibitory surround called NCRF (non-classical receptive field) and a central region called CRF (classical receptive field). The stimulus sensed by NCRF always weakens the CRF’s response to the stimulus in the central region. In the synthesized image Fig. 1(b), the sensations of the central points in region A, B, and C are suppressed by their surrounds.

The effect is strong in texture region B because its surround is full of textures, whereas the boundary regions A and C are less affected. Thus, the boundaries in A and C are highlighted. Some of the researchers have applied the surround suppression mechanism to contour detection. In this application, the suppression process was embedded in the Canny edge detection operator to emphasize the detection of contour edges of objects. We extract some critical steps of the method in the literature to suppress the texture gradients for our diffusion equation. The extracted suppression procedure for the gradient module $|\nabla I(x,y)|$ of an image is expressed as follows:

1. First, the suppression surround is simulated by constructing a suppression weighting function. Let $D_\sigma G_\sigma(x,y)$ be the following difference between two Gaussian functions with the scale $\sigma$:

$$D_\sigma G_\sigma(x,y) = \frac{1}{2\pi(4\sigma^2)^{3/2}} \exp \left(-\frac{x^2 + y^2}{2(4\sigma^2)}\right) - \frac{1}{2\sigma^2} \exp \left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$  \hspace{1cm} (3)

The negative values in $D_\sigma G_\sigma(x,y)$ are set to 0, and normalization is performed to obtain the weighting function $w_\sigma(x,y)$:

$$w_\sigma(x,y) = \frac{H[D_\sigma G_\sigma(x,y)]}{\text{sum}(H[D_\sigma G_\sigma(x,y)])}$$  \hspace{1cm} (4)

Where

$$H[z] = \begin{cases} 0, & z < 0 \\ z, & z \geq 0 \end{cases}$$  \hspace{1cm} (5)

The operator sum ($) in (4) denotes a summation. The region with positive values in $w_\sigma(x,y)$ approximates an annular suppression surround.

2. Then, the suppression term $t(x,y)$ for each pixel is calculated by convolving the gradient module with the weighting function $w_\sigma(x,y)$:
In practice, the above convolution can be performed as a multiplication in the Fourier domain to reduce the computational complexity.

3. Finally, the suppressed gradient values \( B(x,y) \) obtained by subtracting the suppression term from the gradient module \( |\nabla I(x,y)| \)

\[
B(x,y) = \nabla[I(x,y)] - a \cdot t(x,y)
\]  

(7)

The suppression mechanism takes effect in such a way that the suppression terms \( t(x,y) \) are small for the boundary edges and large for the texture edges. Here, \( B(x,y) \) is the suppression strength factor, which directly influences the suppression effect.

c). Proposed Method for Illumination Estimation

From introducing the texture suppression in the previous subsection, the proposed nonlinear diffusion equation for illumination estimation is now given as

\[
\begin{align*}
\frac{\partial L(x,y,t)}{\partial t} &= \text{div}(g[B(x,y)] \cdot \nabla L(x,y)) \\
L(x,y,0) &= S(x,y)
\end{align*}
\]  

(8)

where \( L(x,y) \) is the illumination image. The boundary template \( B(x,y) \) is computed by performing suppression on the illumination gradient \( |\nabla L(x,y)| \) using the method given in Section II-B. It replaces the former gradient module to be the new criterion for selective smoothing. The initial image for the iterations is set as the original degraded image \( S(x,y) \).

Now that \( B(x,y) \) can differentiate the texture edges and boundary edges, the conductance function \( g(.) \) in equation (8) is required to have a threshold property. It should be large where \( B(x,y) \) is small, and vice versa. This approach will separate the diffusivities between the boundary areas and non-boundary areas. We refer to the analysis and slightly modify Tukey’s biweight function to be the conductance function:

\[
g(x) = \begin{cases} 
0.92 \cdot \left(1 - \left(\frac{x}{K}\right)^2\right) + 0.08 & x \leq K \\
0.08 & x > K
\end{cases}
\]  

(9)

where \( K \) is the threshold that differentiates the boundary edges from the suppressed texture edges. To achieve consistency in the whole diffusion process, \( K \) should be set as an adaptive threshold. Our tests show that when \( K \) is set to be equal to the 90% - 95% value of the cumulative distribution function of \( B(x,y) \), the estimated illumination is correct. The small value 0.08 is added to prevent an absolute diffusion shutoff, which causes unnaturalness around some of the slowly varying boundaries. Considering that the reflectance is always below 1, during the diffusion process, the constraint \( L > S \) (i.e., the illumination is greater than the luminance) should be imposed at each iteration. One of the explicit schemes is expressed as follows:

\[
L^{k+1}_s = L^k_s + \tau \cdot \sum_{p \in N_e(s)} \frac{g^k_s + g^k_p}{2} \cdot (L^k_p - L^k_s)
\]  

(10)

Where

\[
g^k_s = g[B^k_s]
\]  

(11)

In (11), \( B^k_s \) denotes the boundary template at pixel \( s \) at the kth iteration. It gives the diffusivity \( g^k_s \) via the conductance function. In (10), \( L^{k+1} \) and \( L^k \) denote the illumination values at pixel \( s \) at the k+1th and kth iterations, respectively. \( N_e(s) \) denotes the 4 neighboring pixels that are connected to pixel \( s \). \( \tau \) is the discretized time step, which is limited to being below 0.2 for stability. For an image of size mxn, the scheme (10) can be rewritten in a matrix-vector notation [26]:

\[
L^{k+1} = L^k + \tau \cdot A(L^k) \cdot L^k
\]  

(12)
In this formation, \( L^{k+1} \) and \( L^k \) are \( mn \times 1 \) column vectors. \( A(L^k) \) is a diffusive matrix of size \( mn \times mn \), with its elements \( a_{sp}L^k \) expressed as

\[
a_{sp}(L^k) = \begin{cases} 
\frac{(a_l + a_p)}{2}, & p \in N_s(s) \\
\frac{(a_l + a_p)}{2}, & p = s \\
0, & \text{elsewhere}
\end{cases}
\]  

(13)

Last but not least, it is necessary to settle the number of iterations \( \omega \) to gain smoothness that is consistent with the illumination assumption, namely, flatness inside regions and discontinuity across region boundaries. Therefore, it is reasonable to stop the diffusion when only the texture areas are wiped out.

We set a stopping criterion as

\[
\frac{\|w_t \cdot (L^{k+1} - L^k)\|}{\|w_t \cdot L^k\|} \leq 7 \times 10^{-6}
\]  

(14)

where \( \| \cdot \| \) denotes the L2 norm operator. Here, \( w_t \) is a weight function described as

\[
w_t = \frac{t_1(x,y)}{\max [t_1(x,y)]}
\]  

(15)

Here, \( t_1(x,y) \) is the suppression term (6) at the first iteration. As described in Section II-B, \( t_1(x,y) \) is especially large in the texture regions, and therefore, the weight \( \varphi \) strengthens those areas. To summarize the discussion above, let \( \varphi \) be the original image, and let \( L \) be the illumination image to be estimated. Then, the procedure of the proposed method is given as

Step1: Initialize \( L^0 = S \).

Step2: Calculate the gradient module of \( L^k \) and perform texture suppression introduced in Section II-B to obtain the boundary template \( B_k \).

Step3: Substitute \( B_k \) into \( g(.) \) and bring forth \( L^{k+1} \) using the explicit scheme as in (12).

Step4: Apply the constraint \( L^{k+1} = \max (S, L^{k+1}) \).

Step5: If \( L^{k+1} \) meets the stopping criterion (14), then execute Step 6. Otherwise, repeat step2 to step5.

Step6: \( L = L^{k+1} \). The estimation is completed.

d). Acceleration for Estimation

Directly applying the explicit scheme in (12) for the diffusion process suffers from an extremely large number of iterations because of the strictly limited time step \( \tau \). Two methods are available to accelerate the estimation: the AOS (Additive Operator Splitting) scheme, to increase the update amount of each iteration, and the multi-resolution technique, to reduce the data complexity.

1) AOS Scheme

Unlike the explicit scheme in (12), a semi-implicit scheme has the following equation:

\[
L^{k+1} = L^k + \tau \cdot A(L^k) \cdot L^{k+1}
\]  

(16)

The difference is that in (16), the data at the \( k+1 \)th iteration consists in both sides of the equation. Then, (16) requires solving a linear system, which gives implicit equations. Ultimately, the general semi-implicit scheme can be synthesized as

\[
L^{k+1} = (E - \tau \cdot A(L^k))^{-1} \cdot L^k
\]  

(17)

where \( \epsilon \) is the \( mn \times mn \) unit matrix.

Because the general semi-implicit scheme requires a large-scale matrix computation, its split versions are much more efficient. One of the split implementations is the AOS algorithm, which is generally expressed as

\[
L^{k+1} = \frac{1}{2} \sum_{d=1}^{2} (E - 2\tau \cdot A_d(L^k) \cdot L^k) \cdot L^k
\]  

(18)

The AOS algorithm first performs 1-D diffusion in both the horizontal and vertical directions separately to obtain the two intermediate results, \( L^{k+1} \), then obtained by taking the average of the two intermediate results. \( A_d(L^k) \) denotes the general diffusive operator in the \( d \)th direction.
The main updating procedure of the AOS scheme for the estimation is concisely stated below; for more details, one can refer to research. For an image of size $m \times n$, we have the following:

1. **Horizontal diffusion.**

The 1-D horizontal diffusion involves calculating a linear matrix-vector equation for each image row independently, as follows:

$$
(E - 2\tau \cdot A_{\text{row},i}^k)g_i^{k+1} = g_i^k, \quad i = 1, 2, 3, ..., m
$$

(19)

where $L_i^k$ and $L_i^{k+1}$, respectively, denote the $i$th row vectors of the smoothed image at the $k$th and $(k+1)$th iterations. In practice, they are transposed before the calculation. $E$ is the unit matrix. $A_{\text{row},i}^k$ is the diffusive matrix operator for the $i$th row and is given as:

$$
A_{\text{row},i}^k = \begin{bmatrix}
     a_1^i & b_1^i & 0 & ... \\
     c_1^i & a_2^i & b_2^i & 0 & ... \\
     0 & ... & 0 & ... \\
     ... & 0 & c_{n-1}^i & a_n^i & b_n^i \\
     ... & 0 & c_n^i & a_n^i & \\
\end{bmatrix}
$$

(20)

where

$$
\begin{align*}
    a_l^i & = -\left(g_{i,l+1}^k + g_{i,l}^k\right)/2, & l & = 1 \\
    a_l^i & = -\left(g_{i,l+1}^k + g_{i,l}^k + 2g_{i,l}^k\right)/2, & l & = 2, ..., n-1 \\
    a_l^i & = -\left(g_{i,l+1}^k + g_{i,l}^k\right)/2, & l & = n \\
    b_l^i & = \left(g_{i,l+1}^k + g_{i,l}^k\right)/2, & l & = 1, ..., n-1 \\
    c_l^i & = \left(g_{i,l+1}^k + g_{i,l}^k\right)/2, & l & = 2, ..., n
\end{align*}
$$

(21)

Here, $g_{i,l}^k$ is the diffusivity at pixel $(i,l)$. It can be seen that the operator is a tridiagonal matrix, and thus $(E - 2\tau \cdot A_{\text{row},i}^k)$ is also tridiagonal. After the row diffusion, each row vector is recombined to form the row-diffused image $L_i^{k+1}$:

$$
\left(E - 2\tau \cdot A_{\text{row},i}^k\right)g_i^{k+1} = g_i^k, \quad i = 1, 2, 3, ..., n
$$

(22)

Similarly, equation (22) is solved via the Thomas algorithm. The diffused column vectors are then combined to form the column-diffused image $L_y^{k+1}$:

$$
A_{\text{col},j}^k = \begin{bmatrix}
     a_1^j & b_1^j & 0 & ... \\
     c_1^j & a_2^j & b_2^j & 0 & ... \\
     0 & ... & 0 & ... \\
     ... & 0 & c_{m-1}^j & a_m^j & b_m^j \\
     ... & 0 & c_m^j & a_m^j & \\
\end{bmatrix}
$$

(23)

Where

$$
\begin{align*}
    c_l^j & = (g_{j,l+1}^k + g_{j,l}^k)/2, & l & = 1, ..., m-1 \\
    c_l^j & = (g_{j,l+1}^k + g_{j,l}^k)/2, & l & = m \\
    b_l^j & = (g_{j,l+1}^k + g_{j,l}^k)/2, & l & = 1, ..., m-1 \\
    c_l^j & = (g_{j,l+1}^k + g_{j,l}^k)/2, & l & = 2, ..., m
\end{align*}
$$

(24)

3. **Averaging.**

Last, the smoothed image of the $(k+1)$th iteration is obtained by averaging $L_x^{k+1}$ and $L_y^{k+1}$:

$$
L^{k+1} = (L_x^{k+1} + L_y^{k+1})/2
$$

(25)

The time step $\tau$ in the AOS scheme is usually set to 5 to achieve a tradeoff between the speed and accuracy. For the setting in the proposed illumination estimation, there is no strict demand for accuracy because coarse smoothness is tolerated as long as the boundary edges are preserved. $\tau$ is set to 15 in this paper.

2) **Multi-resolution Technique**
Multi-resolution processing is an effective way to reduce the computation complexity because the computation is focused on a lower resolution that has a smaller data size yet remains the main structure of the original image. We simply decimate the image by a factor of 2 repeatedly to form the multi-resolution pyramid hierarchy, then start estimating the illumination at the coarsest resolution and expand the result by interpolation to be the initial image for the next resolution. To prevent excessive loss of the boundary information, the number \( N \) of downsampling is set in such a way that the size of the coarsest resolution is no smaller than 200:

\[
N = \text{floor}\left[\log_2\left(\frac{\text{max}(rn, cn)}{200}\right)\right]
\]

where \( rn \) and \( cn \) are the sizes of the rows and columns, respectively, and floor[.] is the down integral function.

\[
L_n = (1 - w) \cdot L_{1n+1} + w \cdot S_n
\]

Where \( L_n \) is the image to be initialized at the \( n \)th layer. \( L_n \) is obtained by taking the weighted sum of the interpolated illumination \( L_{1n+1} \) at the end of the coarser \( n+1 \)th layer and the original image \( S_n \) at the \( n \)th layer. The weight \( w \) is calculated by normalizing the boundary template \( B_{1n+1} \) of \( L_{1n+1} \).

\[
w = \frac{B_{1n+1}}{\text{max}(B_{1n+1})}
\]

It can be seen that \( w \) is large in the boundary areas, and thus, the sharp boundary edges in \( S_n \) replace the blurred counterparts in \( L_{1n+1} \).

In applications that utilize both the AOS scheme and multi-resolution technique, the number of iterations deployed in each resolution is settled based on two principles: 1) The total number of iterations is 10. 2) The finest resolution (original image) has 0 iterations. The remaining levels except for the coarsest level have 1 iteration, and the coarsest level has the remaining iterations.

e). Discussion about Well-posedness

As mentioned earlier, there is potential concern for ill-posedness of the nonlinear diffusion. In theory, the ill-posedness causes both forward and backward diffusions in the iterative process, which influences its convergence to a globally constant solution. discretization scheme of the equation. As was verified, for a discretization procedure as follows

\[
S^{k+1} = Q(S^k) \cdot S^k
\]

if \( Q(.) \) has such properties as continuity, non-negativity, symmetry, unit row sum, positive diagonal elements and irreducibility, then the diffusion filtering creates a smoothing scale space that guarantees convergence to a constant solution as the number of iterations tends to infinity. The former two conditions are inherited directly from the conductance function, whereas the latter four are related to the intrinsic structure of the discretization scheme.
Fig. 4.7. Contribution of texture suppression. (a) Original image. (b) Illumination without texture suppression. (c) Reflectance without texture suppression. (d) Enhanced image without texture suppression. (e) Illumination with texture suppression. (f) Reflectance with texture suppression. (g) Enhanced image with texture suppression. (h) Curves of average local entropy of two illuminations

III. PROPOSED CONTRAST ENHANCEMENT ALGORITHM

The procedures of the proposed algorithm mainly involve illumination estimation, illumination-reflectance decomposition, illumination adjustment, and recombination of the two components. This type of structure addresses the illumination problem effectively and is widely adopted in variational Retinex algorithms. Note that our algorithm generally differs in two aspects: 1) the method for illumination estimation is via nonlinear diffusion; and 2) the mapping function for illumination adjustment is a logarithmic function.

Fig. 3 presents the procedure of the core enhancement process for the luminance component (i.e., the V component in HSV) of the image. In the decomposition process, the illumination component \( L(x,y) \) of the image luminance \( S(x,y) \) is first estimated using the nonlinear diffusion method provided in Section II-C, and then, the reflectance image \( R(x,y) \) is obtained \( S(x,y) \) by dividing \( L(x,y) \).

\[
R(x,y) = \frac{S(x,y)}{L(x,y) + \delta}
\]  

(30)

where \( \delta \) is a small value that avoids division by 0. As the textures are smoothed out in the illumination, they are stored in reflectance via the division. This step is crucial for the final local contrast enhancement.

Then, the illumination image \( L(x,y) \) is adjusted by a mapping function. Because the logarithmic function is strongly correlated to the nonlinear response of the human eye to the luminance, the adjustment is given as

\[
L_a(x,y) = \log_2(L(x,y) + 1)
\]  

(31)

In practice, the log function has strong compression while preserving the brightness order, which makes the enhanced image look natural. This step is important for elevating the global brightness. The adjusted \( L_a(x,y) \) is then multiplied by the reflectance image \( R(x,y) \) again to obtain the adjusted luminance \( S_a(x,y) \)

\[
S_a(x,y) = R(x,y) \cdot L_a(x,y)
\]  

(32)

Next is the histogram clipping step, which cuts 0.5% of the pixels at the two ends of the histogram. This process can both remove the influence of a few pixels that have extreme luminance values and slightly enhance the image contrast. The last step is to rescale the dynamic range to [0 255] to obtain the enhanced luminance \( S_e(x,y) \).

IV. RESULTS AND DISCUSSIONS

Introduction

In this chapter, results of the contrast enhancement by using nonlinear diffusion filtering and large histogram modification are discussed.

SOURCE IMAGES

The image is collected as the input image in which the image is taken in Delhi. The input image is shown in the figure 6.1. Size of the input image is 3.29MB with a resolution of 2000×1312 pixels, which is in jpg format.

Figure 6.1: Input image of house.png
Figure 6.2: Output image of Non linear diffusion

Figure 6.3: Output image of Gradient image

Figure 6.4: Original image

The input image is shown in the figure 6.1. Size of the original image is shown in the figure 6.4, 20KB with a resolution of 420×341 pixels, which is in jpg format.

Figure 6.5: Output image of Illumination image

Figure 6.6: Output image of Non linear diffusion gray conversion

The image is collected as the input image in which the image is taken in Delhi. The output image is shown in the figure 6.6. Size of the output image is 16kb with a resolution of 420×364 pixels, which is in jpg format.

Figure 6.7: Output image of Non linear output

The image is collected as the input image in which the image is taken in Delhi. The output image is shown in the figure 6.7. Size of the output image is 24kb with a resolution of 420×341 pixels, which is in jpg format.
Figure 6.8: Output image of Existing method multi scale retinex

NONLINEAR DIFFUSION FILTERING

Input Image:

The image is collected as the input image in which the image is taken in Delhi. The input image is shown in the figure 6.9. Size of the input image is 64kb with a resolution of 540×720 pixels, which is in jpg format.

Figure 6.9: Input image of gen05.jpg at Imt manesar, gurgaon

Output Images

Figure 6.10: Output image of Nonlinear diffusion Filtering

The output image is shown in the figure 6.10. Size of the output image is 44kb with a resolution of 561×420 pixels, which is in jpg format.

The image is collected as the input image in which the image is taken in Delhi. The output image is shown in the figure 6.11. Size of the output image is 20kb with a resolution of 561×420 pixels, which is in jpg format.

Figure 6.11: Output image of Grad. Magnitude

LARGE HISTOGRAM MODIFICATION

Input Image

The image is collected as the input image in which the image is taken in Delhi. The input image is shown in the figure 6.12. Size of the input image is 64kb with a resolution of 540×720 pixels, which is in jpg format.
Figure 6.12: Input image of gen05.jpg at Imt manesar, gurgaon in Delhi

Output Image

The image is collected as the input image in which the image is taken in Delhi. The output image is shown in the figure 6.13. Size of the output image is 28.7kb with a resolution of 525x566 pixels, which is in jpg format.

Figure 6.13: Output image of Large Histogram Modification

V. CONCLUSION AND FUTURE SCOPE

CONCLUSION

This project discussed the issue of illumination estimation in many enhancement algorithms that are based on illumination-reflectance decomposition. An assumption for the expected illumination that avails the contrast enhancement is also specified. A method based on nonlinear diffusion is proposed to realize the correct illumination estimation. This method solves the problem of the limited contrast enhancement that results from the low smoothing capability of a traditional nonlinear filter. The analytical experiments show that the proposed enhancement algorithm achieves better visual quality than previous algorithm. The acceleration methods enable the algorithm to have high computational efficiency. However, color management is not involved in this paper. In some special cases in which the scene is illuminated by a colored ambient light, balancing the image color is required. Because directly extending our algorithm to three color channels would cause a graying-out effect, more work should be performed in this area. This challenge will be our future work.

FUTURE SCOPE

There are several future works to resolve. With the help of proposed work we can further use it for different applications like Image Segmentation, Image Video processing, object tracking, object recognition, etc.

REFERENCES